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# Performance of Factors and Application of Graph Neural Networks in Landslide Susceptibility Assessment: A Case Study in Taiwan

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ABSTRACT: Taiwan's complex geology, steep topography, and frequent intense rainfall make it highly susceptible to landslides, particularly in mountainous regions. Traditional landslide susceptibility assessment (LSA) models often treat slope units as independent entities, overlooking the spatial dependencies critical to understanding landslide mechanisms and slope stability. This study introduces a Graph Neural Network (GNN) approach that explicitly models spatial adjacency among slope units, thereby capturing the interconnected nature of landslide processes. Focusing on the Chenyulan, Laonong, and Qishan River watersheds—areas recognized for their high landslide risk—the research uses slope units as graph nodes, assigns landslide conditioning factors (including lithology, slope, curvature, land cover, and rainfall indices) as node features, and encodes spatial relationships as graph edges. The GNN model was trained to learn from both the features of individual units and their spatial relationships, allowing it to identify clusters of landslide-prone terrain. Its performance was evaluated against a baseline Random Forest (RF) model previously applied in the same regions. Results show that the GNN produces more spatially coherent and extensive susceptibility predictions, closely aligning with field-observed landslide distributions and effectively reflecting the occurrence of larger-scale landslide events. The GNN achieved an overall accuracy exceeding 80%, with precision around 70%, though recall was moderate (30-60%), indicating some difficulty in detecting isolated landslide events. These results highlight the GNN's ability to capture spatial correlations and improve the reliability and interpretability of LSA outputs. By explicitly addressing spatial dependencies, this research provides a robust and scalable methodology for landslide hazard mapping in Taiwan, offering a reference framework for similar applications in other landslide-prone regions.

KEYWORDS: Landslide, landslide potential, spatial adjacency, graph neural network, machine learning.

## 1 INTRODUCTION

Landslides represent one of the most prevalent and destructive natural hazards in mountainous regions, particularly where geological and climatic conditions converge to create unstable terrain. Taiwan is especially vulnerable due to its location at the boundary of the tectonic plates. This tectonic setting results in intricate lithological formations, frequent seismic activity, and steep topography. Combined with intense monsoonal and typhoon-driven rainfalls, these factors contribute to the frequent occurrence of slope hazards and disasters across Taiwan. The increasing intensity and unpredictability of such events, further intensified by climate change and human-induced land-use changes, underscore the urgent need for advanced and reliable landslide susceptibility assessment (LSA) methods. Traditional LSA approaches, including statistical analyses and physically based models, have provided the foundation for hazard mapping.

Foundational studies by Guzzetti et al. (1999, 2000) emphasized systematic landslide mapping and multi-scale factor analysis. Grelle et al. (2014) integrated probabilistic and deterministic models, focusing on rainfall-induced landslides, and highlighted hydrological factors such as initial water table conditions. Qi et al. (2024) evaluated 17 ML models in tectonically active areas, stressing the importance of model selection and factor analysis. El Jazouli et al. (2022) found that Random Forests (RF) generally outperform Support Vector Machines (SVM) in capturing complex interactions. Lee et al. (2024) advanced ensemble and stacking methods, combining multiple models to enhance robustness and accuracy. These findings indicate that no single model is universally best; combining models often yields superior results.

However, many of these approaches treat slope units as independent entities, overlooking the spatial correlations and interactions among neighboring terrain features that are often critical for understanding landslide mechanisms. While machine learning (ML) and deep learning (DL) models have enhanced prediction capabilities by capturing nonlinear relationships among landslide conditioning factors, they often still assume spatial independence, which limits their effectiveness in spatially interconnected landscapes, such as those in Taiwan. Recent developments in spatial deep learning have introduced Graph Neural Networks (GNNs) as a promising approach to address these limitations.

A transformative development in LSA is the use of Graph Neural Networks (GNNs), which explicitly model spatial dependencies by representing slope units as graph nodes connected by edges denoting spatial adjacency or environmental similarity. Zhang et al. (2024) constructed graphs based on both spatial and environmental similarity, improving prediction accuracy. Zeng et al. (2022) introduced environmental consistency constraints in GNNs to ensure the generation of plausible predictions. Previous studies have demonstrated that GNNs outperform conventional ML models in complex terrains by better preserving the topological and contextual information inherent in geospatial data.

This study applies a GNN-based framework to assess landslide susceptibility in three major watersheds in Taiwan: the Chenyulan, Laonong, and Qishan Rivers. Each slope unit within the study area is defined as a node, characterized by a set of landslide-related factors, including lithology, slope angle, curvature, and land cover. Spatial adjacency among these units is encoded as edges, forming a graph upon which the GNN operates. The model is trained to learn spatially dependent patterns contributing to landslide occurrence.

The performance of the GNN model is compared with that of traditional ML approaches, particularly the Random Forest (RF) model, which has been previously applied in the same regions (Lu, 2021; Huang and Lu, 2021). Preliminary results indicate that the GNN produces more spatially coherent and extensive landslide susceptibility predictions, closely aligning with observed landslide distributions from field surveys. These findings suggest that integrating spatial adjacency into the modeling process can significantly enhance the reliability and interpretability of LSA outputs. The results of this study are expected to support improved disaster risk reduction strategies in Taiwan and provide a reference framework for similar applications in other landslide-prone regions.

## 2 STUDY AREA AND DATABASE

### 2.1 *Study area*

This study focuses on three major river watersheds in Taiwan: the Chenyulan River, Laonong River, and Qishan River watersheds (Figure 1). These regions, located in the central and southern parts of Taiwan, are widely recognized for their high landslide susceptibility due to a combination of complex geological structures, steep topography, and frequent extreme weather events.

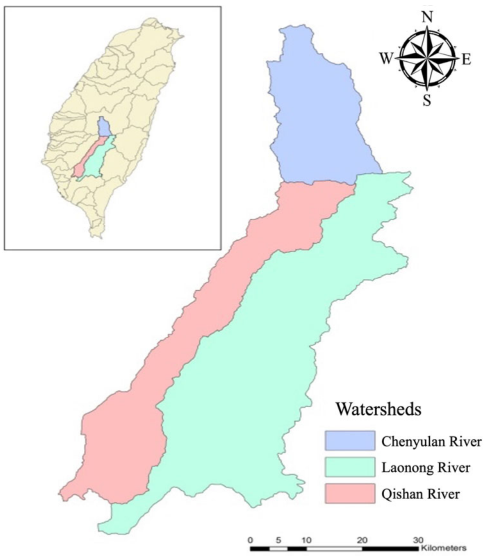


Figure 1. Study area.

Geographically, the Chenyulan watershed in central Taiwan features rugged terrain with deeply incised valleys, while the Laonong watershed, part of the Gaoping River system in the south, exhibits steep slopes and active erosion processes. The Qishan watershed, also located in southern Taiwan, is known for its dynamic landscape shaped by both natural and human-induced influences.

These areas are characterized by steep terrain, fractured rock masses, and unconsolidated soils, which are highly susceptible to slope failure. In addition, both regions experience substantial annual precipitation, often exceeding 2,000 mm, contributing to frequent landslide events. Anthropogenic factors, such as road construction, agriculture, and deforestation, have further destabilized slopes in these regions, thereby amplifying landslide risks.

The geology of the study area encompasses a mix of sedimentary, metamorphic, and occasionally igneous rock formations. In the Chenyulan watershed, rocks from the Lushan Formation and the Miocene strata predominate, whereas in the Laonong and Qishan watersheds, formations from the Western Foothills and Central Range geological zones are more prevalent. These formations often exhibit high degrees of weathering and fracturing, particularly along fault zones, which significantly weaken slope stability.

Vegetation coverage ranges from dense forests in higher elevations to agricultural and urban areas at lower altitudes. Vegetation plays a crucial role in stabilizing slopes by reinforcing the soil and reducing runoff; however, land-use changes and deforestation have locally increased the risk of landslides.

Taiwan's subtropical to tropical climate exposes these watersheds to frequent typhoons, which bring intense rainfall within short durations. Combined with steep slopes and a fragile geologic environment, these conditions result in a high density of historical landslide occurrences.

### 2.2 *Database*

To build a reliable landslide susceptibility model, a detailed database was assembled by integrating multiple spatial and environmental datasets. Digital elevation models (DEMs) provide the basis for extracting elevation, slope, and aspect, which are fundamental topographic variables that influence landslide occurrence. Geological maps supplied information on lithology and structural features that affect slope stability. Hydrological data, including river networks, enabled calculation of the distance from each slope unit to the nearest river channel, an important factor as proximity to rivers often correlates with increased erosion and slope instability. Remote sensing data were used to derive the Normalized Difference Vegetation Index (NDVI), which quantifies vegetation density and health, serving as an indicator of slope reinforcement. Rainfall data, including both long-term averages and event-specific records, were incorporated to capture precipitation's influence on landslide triggering. Recent landslide events identified through remote sensing and field surveys provided measured data for model calibration and validation.

The study area was subdivided into slope units using the method employed by Huang et al. (2019). Each slope unit was assigned a unique identifier, and its centroid was used to spatially link all relevant attribute data from the various datasets. This approach ensured that each slope unit was characterized by a comprehensive set of environmental, geological, and hydrological factors, facilitating detailed and spatially consistent landslide susceptibility analysis.

By integrating these diverse datasets at the slope unit scale, the database establishes a foundation for applying machine learning and graph-based models, such as Graph Neural Networks (GNN), which can effectively capture spatial dependencies and complex factor interactions.

This approach follows the methodology developed by Huang and Lu (2021), who demonstrated the effectiveness of machine learning models, particularly Random Forest (RF). The integration of multi-source data, encompassing topography, geology, hydrology, vegetation, and rainfall, within the Chenyulan, Laonong, and Qishan River watersheds yields a comprehensive and well-organized database for landslide susceptibility modeling.

The watersheds' complex geological environment, steep terrain, and climatic conditions make it an excellent testbed for advanced predictive models that incorporate spatial adjacency and temporal dynamics. This detailed dataset supports the development of more accurate and spatially explicit landslide susceptibility assessments, which can ultimately enhance hazard mitigation and risk management efforts in Taiwan's mountainous regions.

## 3 METHODS

This study focuses on the Chenyulan, Laonong, and Qishan River watersheds in southern Taiwan, regions known for their vulnerability to rainfall-induced landslides, especially during typhoon seasons. To capture the spatial heterogeneity of landslide processes, we employed slope units as the fundamental mapping units. Slope units are defined as contiguous terrain segments bounded by drainage divides and flow lines, each representing a geomorphologically coherent area (Figure 2). Using a combination of high-resolution DEM analysis and hydrological modeling, the Chenyulan River, Laonong River, and Qishan River watersheds are 6651, 21,279, and 10,985 slope units, respectively. The centroid of each slope unit served as the reference point for extracting geospatial attributes.

Another key factor used in this study is the influence of antecedent landslide areas (Huang and Lu, 2021). The types of landslide areas are classified into five types as shown in Figure 3. The total area, labeled as No. 3 and No. 4 in Figure 3, was treated as the new landslide areas during a single period. The ratios related to landslide areas, i.e., the proportions of No. 1, No.2, No. 3, No.4, and No. 5 in Figure 3, were calculated for each slope unit after satellite image processing and interpretation. The condition of a slope unit would be classified as a landslide when the ratio of incremental landslide area (No. 3 + No. 4) was greater than or equal to 5%. The proportion of landslide areas over the past five years and the proportion of landslide areas for the current year were used in the model database. In this study, the 2011 landslide database was utilized to establish the GNN model, while the databases from 2012 to 2016 were used for external testing.

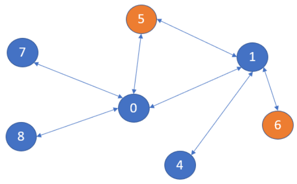


Figure 2. Illustration of the relationship between slope units.

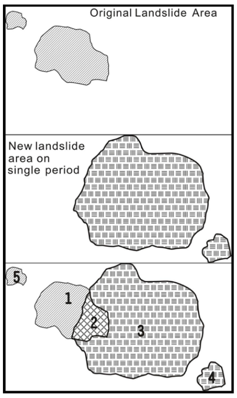


Figure 3. Illustration of mapping landslide areas (Huang et al., 2019).

A comprehensive set of 50 variables was compiled to characterize each slope unit, drawing from previous research in the region (Lu, 2021; Yeh, 2022; Huang, 2023). These variables were grouped into four categories:

1. Topographic factors: elevation, slope, aspect, curvature, and surface roughness.
2. Geological and environmental factors: lithology, land cover classification, normalized difference vegetation index (NDVI), and proximity to river channels.
3. Rainfall indices: maximum hourly rainfall, cumulative rainfall over critical periods, and antecedent precipitation.
4. Antecedent landslide indicators: proportion of SU area affected by landslides in the preceding five years.

All variables were standardized prior to modeling to ensure comparability and reduce bias from differing measurement scales.

To assess landslide susceptibility, we implemented two machine learning frameworks:

1. Random Forest (RF): The RF model, widely recognized for its robustness in handling high-dimensional and nonlinear data, was configured with 500 trees and a maximum depth of 20, following best practices in geospatial modeling. The model treats each slope unit independently, using the full suite of 50 variables as input features.
2. Graph Neural Network (GNN): To explicitly account for spatial dependencies, we constructed a graph where each slope unit is represented as a node, and edges connect adjacent slope units that share a boundary. Node features correspond to the geospatial attributes described above. The GNN architecture, adapted from Huang (2023), consists of three graph convolutional layers, enabling the model to aggregate information from neighboring slope units and capture spatial patterns relevant to landslide occurrence.

Both models were trained and validated using a 70%–30% split of the dataset, ensuring a balanced representation of landslide and non-landslide cases. Performance was evaluated using accuracy, precision, recall, and the Kappa Index of Agreement (KIA), derived from confusion matrices.

## 4 RESULTS AND DISCUSSION

The GNN model, when trained on data from the year 2011, achieved an overall accuracy of 73.9%, with a precision of 64.9%, as shown in Table 1. However, recall was considerably low at 19.4%, reflecting the challenge of detecting all landslide-prone slope units in a dataset where stable units predominate. Notably, the confusion matrix revealed a higher rate of false negatives—slope units susceptible to landslides that were incorrectly classified as stable. This pattern is consistent with the class imbalance inherent in the dataset, where landslide events are relatively rare.

Applying the trained GNN model (using the 2011 dataset) to annual datasets from 2012 to 2016 yielded consistent results (0): accuracy above 80%, and precision was stable at about 70%, but recall fluctuated between 30% and 60%. This suggests that while the model is effective at minimizing false positives, it tends to underpredict the actual number of landslide occurrences.

Spatial analysis highlighted the strengths of the GNN in capturing clusters of landslides. The model excelled at delineating spatially coherent patterns of susceptibility, although it was less effective at identifying isolated or scattered landslide events.

In contrast, the RF model produced more dispersed predictions, with lower precision and higher recall. The GNN's explicit incorporation of spatial adjacency thus contributed to more reliable and operationally useful susceptibility maps.

Table 1. Training results of GNN models using the 2011 database.

| Factor used | ACC | Precision | Recall | Kappa |
|---|---|---|---|---|
| 50 | 0.739 | 0.649 | 0.194 | 0.053 |

By visualizing the model prediction results as landslide maps and comparing them with actual landslide locations, the model's performance can be evaluated. Taking the data from 2012 as an example (Figure 4), a comparison of the landslide predictions from the two models shows that slope units with actual landslides tend to be more densely clustered and more numerous on the map.

Table 2. Comparison of model performance between RF and GNN.

| Year | ACC | | Precision | | Recall | | Kappa | |
|---|---|---|---|---|---|---|---|---|
| | RF | GNN | RF | GNN | RF | GNN | RF | GNN |
| 2012 | 0.781 | 0.846 | 0.474 | 0.733 | 0.838 | 0.389 | 0.466 | 0.387 |
| 2013 | 0.807 | 0.863 | 0.500 | 0.715 | 0.883 | 0.482 | 0.519 | 0.471 |
| 2014 | 0.798 | 0.874 | 0.510 | 0.729 | 0.949 | 0.634 | 0.534 | 0.592 |
| 2015 | 0.715 | 0.895 | 0.310 | 0.678 | 0.973 | 0.361 | 0.340 | 0.388 |
| 2016 | 0.797 | 0.879 | 0.480 | 0.725 | 0.935 | 0.562 | 0.512 | 0.549 |

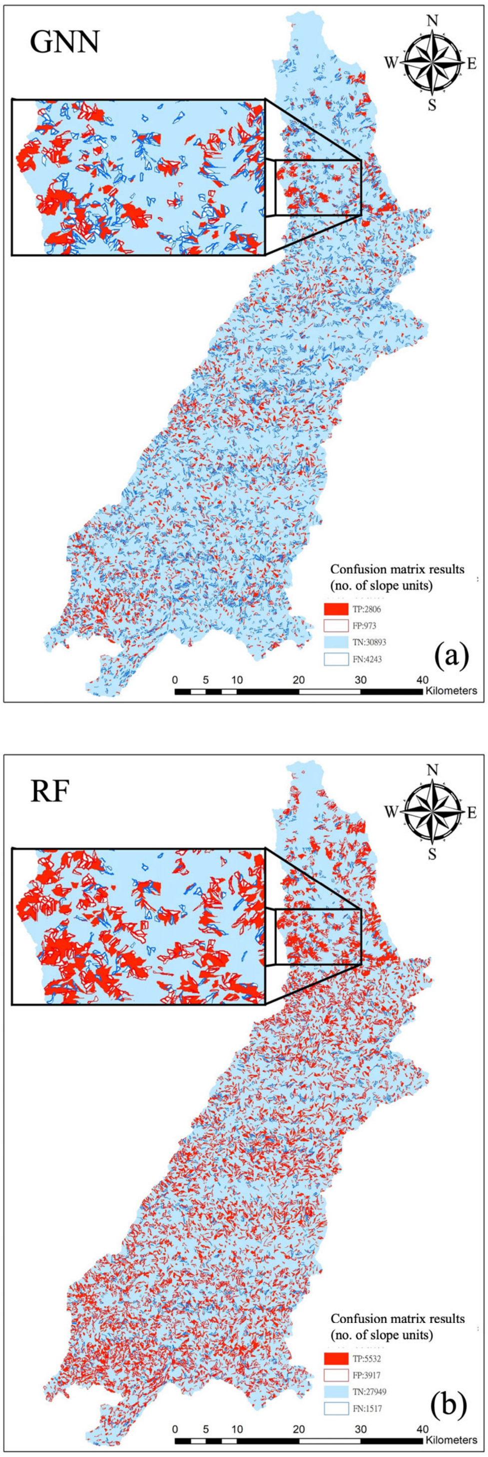


Figure 4. The landslide map of 2012 generated by (a) GNN and (b) RF models.

In contrast, isolated landslide slope units are more likely to be misclassified as non-landslide areas. This is because, through the spatial adjacency relationships, the feature information is propagated among connected slope units, making it easier to extract non-landslide characteristics when a unit is surrounded by more non-landslide neighbors. In addition, the landslide prediction map generated by the GNN closely resembles the distribution of the actual landslide map (event-based, as in Figure 5), showing a clustering pattern of landslides that aligns with on-site observations.

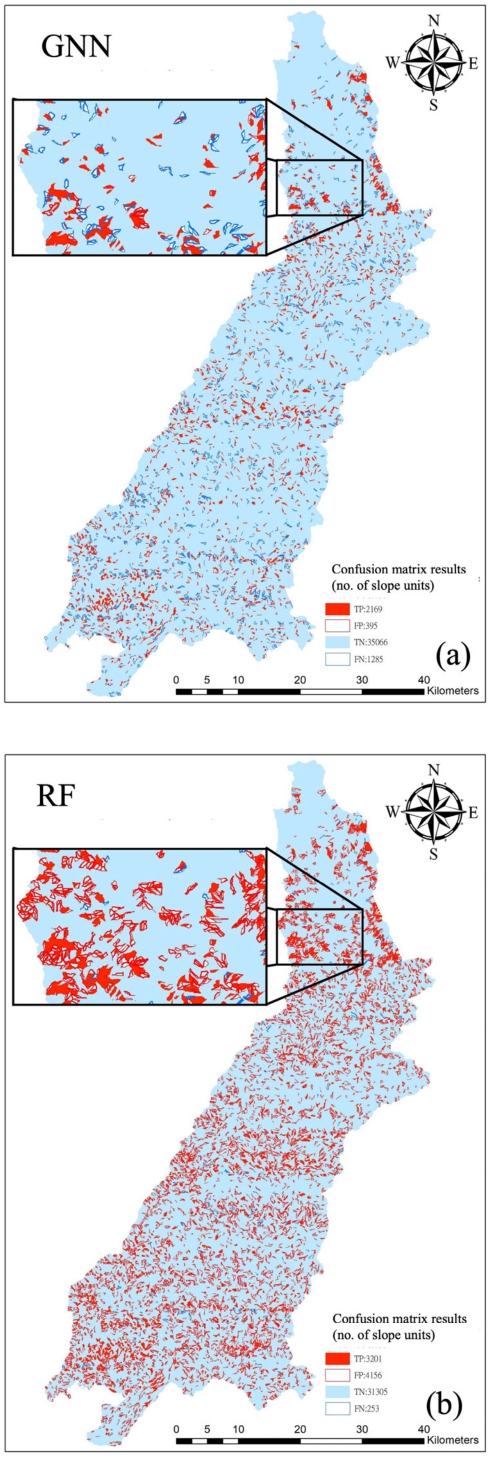


Figure 5. The landslide map of 0601 Hearvy Rainfall in 2017 generated by (a) GNN and (b) RF models.

The results demonstrate that GNNs offer significant advantages for landslide susceptibility mapping in mountainous, spatially complex environments. By leveraging both feature attributes and spatial relationships, the GNN generated susceptibility maps that closely aligned with geomorphological features, such as slope breaks, river incision zones, and lithologic transitions. This spatial coherence is particularly valuable for hazard communication and targeted risk mitigation. However, the model's moderate recall underscores a critical trade-off: while false positives are reduced, some at-risk areas may be overlooked. This limitation is largely attributable to class imbalance, a common issue in geohazard datasets where landslide events are infrequent relative to stable terrain. The tendency to miss isolated landslides suggests that GNNs, while adept at capturing spatial clusters, may underperform in detecting outlier events.

## 5 CONCLUSIONS

This study examines the application of Graph Neural Networks (GNNs) in landslide susceptibility mapping, particularly in Taiwan's mountainous regions, where the spatial relationships between slope units significantly influence landslide occurrence. By modeling adjacency between slope units, the GNN approach captures how the characteristics of neighboring units influence susceptibility, allowing the model to reflect the spatial clustering commonly observed in actual landslide events. This mechanism improves the spatial continuity of predictions and enhances the practical interpretability of the results.

Compared with the Random Forest (RF) model, the GNN achieved higher precision and better spatial consistency, though its recall was more moderate. The RF model, while slightly better at identifying more potential landslide areas (higher sensitivity), also showed a higher false positive rate, which may reduce its usefulness in operational settings. In contrast, the GNN's output was more focused, particularly effective in capturing landslide-prone areas. However, the model's tendency to miss isolated or small-scale events highlights an ongoing challenge related to class imbalance in the training data.

The findings suggest that GNNs are a promising tool for generating landslide susceptibility maps that align with real-world geomorphological features. The inclusion of spatial structure offers a significant advantage in mapping terrain-based hazards. For future development, a combined modeling strategy—using RF for broad screening and GNN for refinement—could further enhance prediction quality. Additionally, incorporating explainable AI tools would make these models more transparent and accessible for use in disaster planning and risk communication.

## 6 ACKNOWLEDGEMENTS

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